RASTER BASED COASTAL MARSH CLASSIFICATION WITHIN THE GALVESTON BAY

ECOSYSTEM, TEXAS

A Thesis

by

ARON SHAUN EDWARDS

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2007

Major Subject: Rangeland Ecology and Management

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Approved by:

Chair of Committee,	James W. Webb, Jr.
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ABSTRACT

Raster Based Coastal Marsh Classification within the Galveston Bay Ecosystem, Texas.

(December 2007)

Aron Shaun Edwards, B.S., Texas A&M University at Galveston

Chair of Advisory Committee: Dr. James W. Webb, Jr.

A mapping study using remote sensing software called ENVI was conducted utilizing four software algorithms to investigate whether these techniques could accurately classify habitat types and vegetation communities along West Bay of the Galveston Bay Ecosystem from color infra-red (CIR) imagery. The algorithms were used in a small-scale study to investigate which of these techniques could most accurately distinguish habitat types and vegetation communities from the imagery at a site specific location. The most accurate algorithm of the four was used in a large-scale classification study in which entire images were classified utilizing the same data from the small-scale study.

Regions of interest (ROIs) were used within ENVI to specify areas of interest within each image that was classified. The locations of ROIs were recorded using a GPS prior to classification, then each was added into ENVI as data points, and each ROI polygon was digitized according to its respective pixel color. Once all of the ROI polygons were completed, each software algorithm was employed.

After classification, each habitat type and vegetation community was ground-truthed in order to verify the accuracy of the algorithms. The position points were added as ground truth points within ENVI and an accuracy matrix was assessed. The technique with the greatest averaged accuracy within the small-scale study was selected for the large-scale study. The ROIs and ground truth points used in the small-scale study were used again in the large-scale study.

The small-scale study concluded that the Parallelepiped algorithm produced significantly less accurate classifications than the other three. Although the Mahalanobis algorithm was not significantly different from the other two algorithms, it yielded the highest overall average accuracy and was used in the large-scale study. In both the small-scale and large-scale studies there was no significant difference in the two different years of aerial imagery and there were no significant differences in accuracy for locations.

None of the software algorithms were accurate at classifying habitat types and vegetation communities using the imagery. The accuracy for the Mahalanobis algorithm was less than 60%. Inaccuracies were largely due to overlapping spectral signatures among habitat types and vegetation communities.

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Secondly, I would not have been able to complete the statistics portion of my research without the assistance of Patricia Edwards. Her time and effort are greatly appreciated for running all of my data through SPSS. I would also like to thank my committee members for aiding me in the drafting and revising stages of my Thesis Proposal and Thesis.

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INTRODUCTION AND OBJECTIVES

The Galveston Bay Estuary (GBE) is the largest and most productive bay system of the Texas coast. Located in the northeastern coast of Texas, GBE hosts a wide variety of ecological and anthropogenic entities, such as the Port of Houston, which is the third largest port in the United States and sixth largest port in the world (Port of Houston Authority, 2003). GBE is ranked as the second most productive estuary in the United States in seafood with commercial fishing producing approximately one-third of the commercial fishing income in Texas (GBEP, 2002). This fisheries industry relies on the GBE ecosystem, which is the sum total of all living things within GBE, their physical environment and the interrelationships among them.

Coastal wetland habitat is a crucial part of the GBE ecosystem providing many benefits for the coastal zone and surrounding areas. Coastal wetlands provide numerous environmental functions to the Bay including water quality maintenance, primary production, ecosystem stabilization, and fish and wildlife habitat (Moulton et al., 1997). Coastal wetland habitat also provides socioeconomic values to the Bay, which includes commercial and recreational fisheries, storm buffering, wastewater treatment, erosion and flood control, and tourism (Moulton, 1997). An estimated 4,105,343 acres of Texas coastal wetland habitat existed in 1955, 15.3% (626,188 acres) being low marsh habitat (Moulton, 1997). By the early 1990s, Texas coastal wetlands had decreased to less than 3.9 million acres, 567,000 (14.5%) acres being low marsh habitat (Moulton, 1997). This shows a loss of approximately 59,000 acres of low marsh habitat in Texas.

GBE is the seventh largest estuary in the United States, consisting of six bays totaling 384,001 acres (Delaney, 2000). In 1993, a study showed that 26,000 acres of low marsh had been transformed from low marsh to areas of water and sand flats (White, 1993). Between 1995 and 2002, estuarine wetlands declined 2,913 acres (Webb, 2005). The loss was primarily due to erosion, which was caused by

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This thesis follows the style of *Wetlands Ecology and Management.*

subsidence. Subsidence of land is the loss of surface elevation due to the removal of subsurface support (The Hartford, 2002). The subsurface support in GBE was groundwater and petroleum and the removal of these fluids has resulted in areas with up to 2.5 meters of subsidence, subsidence fissures 6 centimeters wide, and subsidence faults with 30 centimeters of displacement (The Hartford, 2002). Intertidal, or low marsh vegetation can survive temporary submergence, but if entire plants are submerged for a long period of time they drown and die. When the coastal vegetation dies, leaves and stems no longer reduce wave energy and roots no longer bind sediment, which allows erosion to occur in the immediate area. In GBE, subsidence has caused areas of low marsh, consisting of smooth cordgrass (*Spartina alterniflora)* stands to drown and break apart, or fragment, creating large areas of open water. This fragmentation is of much concern within the coastal wetlands of GBE. If fragmentation occurs in significant amounts, a majority of the GBE coastal wetlands will disappear leading to environmental and socioeconomic consequences.

Computer technology is now allowing users to view, classify, and map the natural environment. The first satellite designed primarily to acquire Earth resource information (ERTS-1), which was later named Landsat, was launched in 1972 (Jensen, 1996). This marked the beginning of a new decade of natural resource data analysis. Since 1972 nearly every habitat type on the Earth has been studied and analyzed using satellite imagery, including grasslands (Atkinson, 2004), mangrove and coastal ecosystems (Saito et al., 2003), agricultural land (South et al., 2004), mountain rangeland (Cingolani et al., 2004), Syrian rangeland (Hirata et al., 2001), and the Brazilian Amazon (Powell et al., 2004). Wetlands have also been intensely studied using remote sensing satellites. Coastal tidal marshes, mangroves, inland freshwater marshes, prairie pothole wetlands, bogs, and fens have all been analyzed (Ozesmi and Bauer, 2002). In the United States, assessing the aerial coverage and health of coastal wetlands has become a priority since the establishment of the Clean Water Act (CWA), more specifically, Section 404 of the CWA, which established a program to regulate the discharge of dredge or fill material into waters of the United States, including wetlands (U.S. Army Corps of Engineers, 1987).

Geographic Information Systems (GIS) have been incorporated in the past because of their extensive capabilities. Manual digitization has been the primary focus of many software packages, including ArcGIS (ESRI, 2005), for wetland mapping. This approach is both expensive and time consuming, depending on the number of analysts working on the project and their expertise in delineating wetlands from aerial images. There are also problems in mapping small communities versus a large community of plants and open sand flats, particularly due to the fact that resolution >1 meter can create overlaps in habitat boundaries when looking at a small community of vegetation. In GBE, many wetland areas have already eroded (Webb, 2005), creating many small areas of low marsh patches, which only adds to the time of digitization. Some researchers have used GIS as a postprocessor to analyze the data once the remote sensing software has completed classification (Hirata, 2001). This creates a hybrid approach, using both remote sensing and GIS to map and analyze natural resources.

Satellite remote sensing is normally used to provide information on particular land uses and their change over time. But because of the low spatial resolution of most satellite imagery (20-30m), it is difficult to classify small or narrow wetlands (Ozesmi and Bauer, 2002). Aerial imagery, on the other hand, can be readily available in high resolutions (1m), come in digital form, and is free of charge from some agencies. Aerial imagery is often preferred over satellite imagery for detailed mapping of wetlands (Ozesmi and Bauer, 2002). Of the different types of imagery, color infra-red (CIR) images can be extremely useful when classifying wetlands. It is also useful in agriculture because the spectral patterns of growing vegetation show a uniquely rapid increase in reflectance near the boundary between the red and near infra-red (NIR) bands (Dalsted and Queen, 2007). Usually, growing vegetation is displayed in red tones on CIR imagery (Dalsted and Queen, 2007). However, in a fragmented marsh, water, vegetation, mud, remaining root masses and organic material can confuse and cause overlapping boundaries by the classification software.

This study will attempt to accurately classify coastal habitat types along West Bay of the GBE using Color Infra-red (CIR) imagery (Figure 1). The Cowardin Classification System (Cowardin et al., 1979), the first nationally recognized wetland classification scheme, which is used by the U.S. Fish and Wildlife Service, will be used as the ecological classifier. The Cowardin system classifies wetlands based on plant characteristics, soils, and frequency of flooding (Jensen, 1996). Five systems form the highest level of classification: marine, estuarine, riverine, lacustrine, and palustrine. The study site will be proposed mainly of estuarine systems, which include two subsystems: subtidal and intertidal. Within the subsystems, classes are based on flooding regime, substrate material, or vegetative life form (Jensen, 1996). The areas of concern within the study site will include sub-tidal deep water (E1UBL), intertidal irregularly exposed unconsolidated substrate (E1UBM) and excavated unconsolidated substrate (E1UBMx), regularly flooded unconsolidated substrate (E1UBN), regularly flooded shoreline (E2USN), irregularly flooded shoreline (E2USP), estuarine low marsh (E2EM1N), irregularly flooded intertidal high marsh (E2EM1P), irregularly flooded scrub shrub composed of high tide bush (*Iva frutescens)* (E2SSP), uplands, composed primarily of coastal prairie (Ur), and urban areas (Uu), composed of commercial/residential buildings (Uub), residential lawns (Uuy), and roads (Uur) (Cowardin et al., 1979). Some of the habitats, such as irregularly exposed shoreline and regularly flooded shoreline, will overlap in some areas, creating errors in the final classification.

This study will also attempt to accurately classify vegetation communities within these habitat types. Species such as smooth cordgrass (*Spartina alterniflora),*leafy three-square *(Scirpus robustus), and* cattail *(Typha sp.)* compose the low marsh, marshhay cordgrass (*Spartina patens),* saltwort *(Batis maritima),* bushy sea ox-eye daisy *(Borrichia frutescens), perennial glasswort (Salicornia virginica),* annual seepweed *(Suaeda linearis),* needlerus*h (Juncus roemerianus),* saltgras*s (Distichlis spicata), and* seashore paspalum *(Paspalum vaginatum)* compose the high marsh, high tide bush (*Iva frutescens)* compose the scrub shrub habitat, and eastern baccharis (*Baccharis halimifolia)* and gulf cordgrass (*Spartina spartinae)* compose the upland range. Each species should have a different spectral signature that the Infrared Scanner should read and differentiate into specific pixel colors. If properly classified, this insight can aid national and state agencies in many ways, including searching for coastal areas that have begun fragmenting or for future marsh transplanting sites.

Study Site

The GBE system consists of six sub-bays: Christmas Bay, West Bay, Lower GBE, Upper GBE, East Bay, and Trinity Bay. The bay is fed by the Trinity River and the San Jacinto River, numerous local bayous and incoming tides from the Gulf of Mexico. GBE covers approximately 600 square miles, and is 30 miles long and 17 miles wide. GBE is on average 7-9 feet deep. The bay has three inlets at the Gulf of

Mexico: Bolivar Roads (the exit of the Houston Ship Channel) between Galveston Island and the Bolivar Peninsula, San Luis Pass to the West, and Rollover Pass to the East.

Figure 1. 1995 TNRIS DOQQ aerial photo of study area

The study site encompasses marshes along West Bay, which includes the Lake Como, Sea Isle, and Hitchcock quadrangles. The area encompasses the West End of Galveston Island, which has changed dramatically in the past 100 years. Large areas of coastal marsh have been dredged in order to create residential developments and associated canals. The coastal marsh on the mainland side of West Bay has not been urbanized, but one area of the marsh has been diked, resulting in a flooding regime. This area will be excluded from the study due to its irregular flooding regime. When the area is flooded it appears to have the same spectral signature as a low marsh, but when not flooded the area takes on the appearance of a coastal prairie.

The estuarine system is composed of open bay waters, irregularly exposed waters that may or may not contain aquatic beds, low marsh consisting primarily of stands of *Spartina alterniflora*; mud and sand flats or areas of no vegetation; high marsh, varying in dominance between *Salicornia virginica, Spartina patens*, *Monanthochloe littoralis, Borrichia frutescens, and Batis maritime*; and unconsolidated shoreline. There is also a large area of urban development including residential and commercial structures. Delineating these areas in the field can be problematic due to an individual's expertise in the area and because the vegetation changes can be very minute and sometimes undetectable on photos.

Objectives and Hypotheses

The primary objective of the present study is to determine whether raster based classification of aerial photography is an accurate procedure for separation of estuarine and coastal prairie habitats within the GBE. Specific objectives are:

1. Determine whether 1995 and 2002 CIR DOQQ imagery at 1 m resolution can be used to distinguish coastal habitat types: permanently flooded unconsolidated bottom (E1UBL); subtidal irregularly exposed unconsolidated bottom (E1UBM) and excavated bottom (E1UBMx); regularly flooded unconsolidated bottom (E1UBN); regularly flooded shoreline (E2USN); irregularly flooded shoreline (E2USP); estuarine low marsh that is regularly flooded, including narrow leaved plants (E2EM1N); irregularly flooded intertidal high marsh (E2EM1P); irregularly flooded scrub shrub composed of *Iva frutescens* (E2SSP); upland range composed primarily of coastal prairie (Ur); urban areas (Uu); commercial/residential buildings (Uub); residential lawns (Uuy); and roads (Uur) utilizing the Parallelepiped Classification Algorithm, Minimum Distance to Means Classification Algorithm, Maximum Likelihood Classification Algorithm, and Mahalanobis Distance Classification Algorithm.
2. Determine whether 1995 and 2002 CIR DOQQ imagery at 1 m resolution can be used to distinguish individual vegetation communities such as *Spartina alterniflora*, *Scirpus robustus*,

and Typha domingensis, which compose the low marsh *Spartina patens*, *Batis maritima, Borrichia frutescens, Salicornia virginica, Suaeda linearis, Juncus roemerianus, Distichlis spicata, and Paspalum vaginatum* which compose the high marsh *Iva frutescens* which composes the scrub shrub habitat and *Baccharis halimifolia* and *Spartina spartinae* which compose the upland coastal prairie utilizing the Parallelepiped Classification Algorithm, Minimum Distance to Means Classification Algorithm, Maximum Likelihood Classification Algorithm, and Mahalanobis Distance Classification Algorithm.

3. Use these data to test the following null hypotheses:

$H_{o,1}$: There are no differences among software algorithms used to classify the habitat types on a small-scale platform.

$H_{o,2:}$ There are no differences among software algorithms used to classify vegetation communities on a small-scale platform.

$H_{o,3:}$ There are no differences between years of imagery used to classify habitat types (on large and small-scale platforms).

$H_{o,4:}$ There are no differences years of imagery used to classify vegetation communities (on large and small-scale platforms).

$H_{o,5:}$ There are no differences among locations when classifying habitat types (on large and small-scale platforms).

$H_{o,6:}$ There are no differences among locations when classifying vegetation communities (on large and small-scale platforms).

MATERIALS AND METHODS

Materials

This study utilized color infra-red (CIR) imagery consisting of 1995 1-meter (m) resolution Digital Ortho Quarter Quads (DOQQs) (Lake Como, Sea Isle, and Hitchcock) that are available from Texas Natural Resource Information Systems (TNRIS) and a 2002 0.5m resolution Texas General Land Office (TGLO) image of Galveston Bay, which was cropped to create panels that entail the same area as the DOQQs. The original 2002 TGLO image was 0.5m resolution, but for computer memory considerations and timeliness of classification, the 2002 cropped images were georeferenced utilizing the Nearest Neighbor referencing system within ENVI (2006). I referenced the 2002 cropped images to the 1995 imagery, which lowered the pixel resolution from 0.5m resolution to 1m resolution and allowed pixels from each time period to align. All of the images utilized the Universal Transverse Mercator (UTM) North American Datum (NAD) 1983 Zone coordinate system.

Raster Classification Methods

Raster classification is the process of assigning specific criteria (e.g. habitat type values) to individual pixels or pixel clusters within an image. Four separate software algorithms were used in the present study, Parallelepiped Classification Algorithm, Minimum Distance to Means Classification Algorithm, Maximum Likelihood Classification Algorithm, and Mahalanobis Distance Classification Algorithm. Each technique was used for the classification of each image using ENVI.

The Parallelepiped Classification Algorithm is a widely used decision rule based on simple Boolean "and/or" logic. Brightness values from each pixel of the imagery are used to produce an n-dimensional mean vector (Jensen, 1996). Boundaries are created which form an n-dimensional parallelepiped in feature space. If the pixel value lies above the lower threshold and below the high threshold for all n bands evaluated, it is assigned to that class. When a pixel does not meet any of the Boolean logic criteria, it is assigned to an unclassified category. It is a computationally efficient method of classifying remotely sensed data, but because some parallelepipeds overlap, sometimes an unknown pixel might satisfy the criteria of more than one class.

The Minimum Distance to Means Classification Algorithm is a decision rule that is computationally simple and commonly used (Jensen, 1996). It requires that the user provide the mean vectors for each class in each band from the training data. The program must calculate the distance to each mean vector from each unknown pixel, which can be done by using Euclidean distance based on the Pythagorean Theorem. Many minimum distance algorithms let the user specify a distance from the class mean beyond which a pixel will not be assigned to a category even though it is nearest to the mean of that category (Jensen, 1996).

The Maximum Likelihood Classification Algorithm assigns each pixel having pattern measurements or certain features to the class whose units are most probable or likely to have given rise to that feature vector (Jensen, 1996). It assumes that the training data statistics for each class in each band are normally distributed. This method involves considerable computational effort because it calculates large amounts of information on the class membership characteristics of each pixel.

The Mahalanobis Distance Classification Algorithm is a direction sensitive distance classifier that uses statistics for each class. It is similar to the Maximum Likelihood Classification Algorithm but assumes all class co-variances are equal and therefore is a faster method. All pixels are classified to the closest region of interest class unless the user specifies a distance threshold, in which case some pixels may be unclassified if they do not meet the threshold.

Small-Scale Classification Algorithm Study

A small-scale study was performed to distinguish the most accurate classification technique, and all four software algorithms were employed on the imagery. The small-scale study was composed of two separate assessments. The first part of the study tested whether pixel colors of vegetation communities could be observed and accurately classified within selected areas rather than the entire DOQQ. The second part of the study examined whether habitat types could be separated and accurately classified within the same selected areas. Regions of interest (ROIs) are used within ENVI to specify classes within each image that is classified. The ROIs for vegetation community separation included the low marsh species *Spartina alterniflora, Scirpus robustus,* and *Typha domingensis*; high marsh species of *Spartina patens, Batis maritima, Borrichia frutescens, Salicornia virginica, Suaeda linearis, Juncus roemerianus, Distichlis spicata*, *Paspalum vaginatum*, *Iva frutescens*; and coastal prairie species of *Baccharis halimifolia* and *Spartina spartinae*. Individual habitat type ROI classes were designated as E1UBL, E1UBM, E1UBMx, E1UBN, E2USN, E2USP, E2EM1N, E2EM5N, E2EM1P, E2SSP, Ur, Uu, Uub, Uuy, and Uur, which were established by Cowardin et al. (1979).

The location of ROIs was recorded using a Trimble XP Handheld global positioning system (GPS) prior to classification. Six areas within the study site (2 areas on the mainland: Hitchcock Quad and 4 areas on Galveston Island: Lake Como and Sea Isle Quads), which included random habitat types, were chosen to conduct the preliminary study. A minimum of two points were chosen for each vegetation community and each designated habitat type within each area (Figure 2). Once the location of ROIs was taken by GPS, each was added into ENVI as data points and each ROI polygon was manually digitized according to its respective pixel color (Figure 3). Once all of the ROI polygons were completed, each software algorithm was employed (Figure 4).

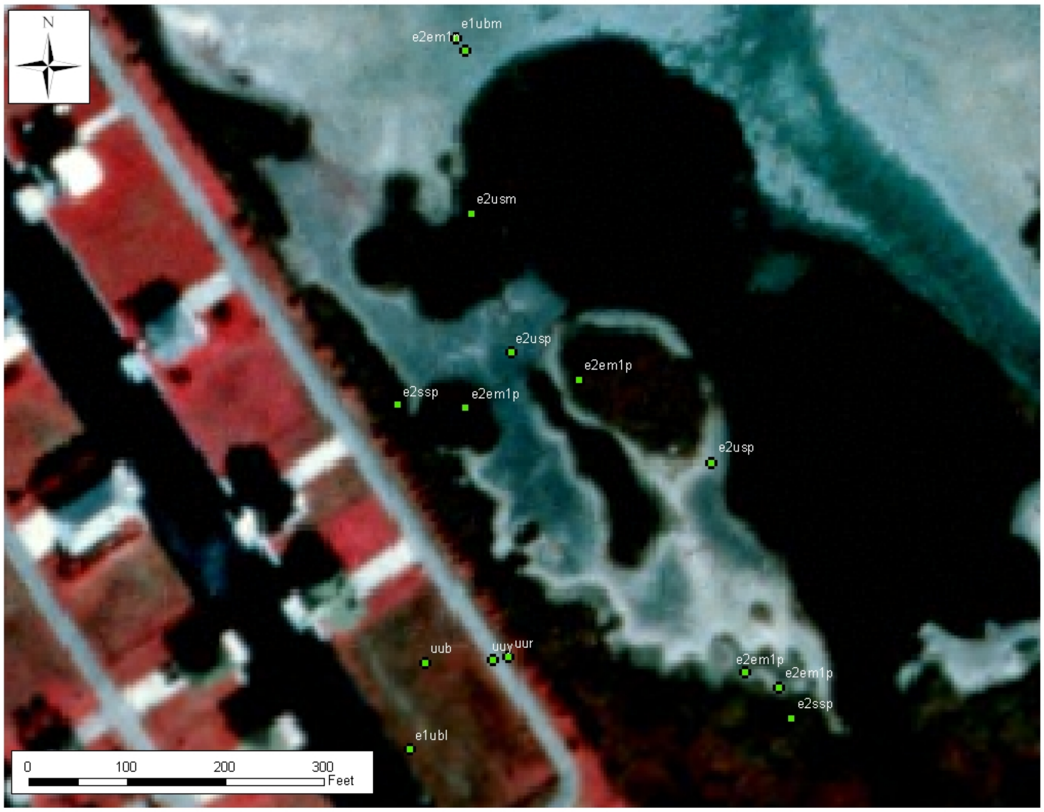


Figure 2. 1995 TNRIS DOQQ photo of Southeast Sea Isle quad with labels on habitat types that were used as ROIs after recording the location with a GPS.

Figure 3. 1995 TNRIS DOQQ photo of Southeast Sea Isle quad with pixel colors of each habitat type manually digitized as ROI polygons. (dark blue – E1UBL, light Blue – E1UBM, orange – E2USN, yellow – Upland, dark green – E2EM1N, light green – E2EM1P)

Once the classification maps were completed, each habitat type and vegetation community was ground-truthed in order to verify the accuracy of the software algorithms. A minimum of two ground truth points were taken for each habitat type and vegetation community for each zoomed in area. Once collected the position points were added as ground truth points within ENVI and an accuracy matrix was assessed within ENVI.

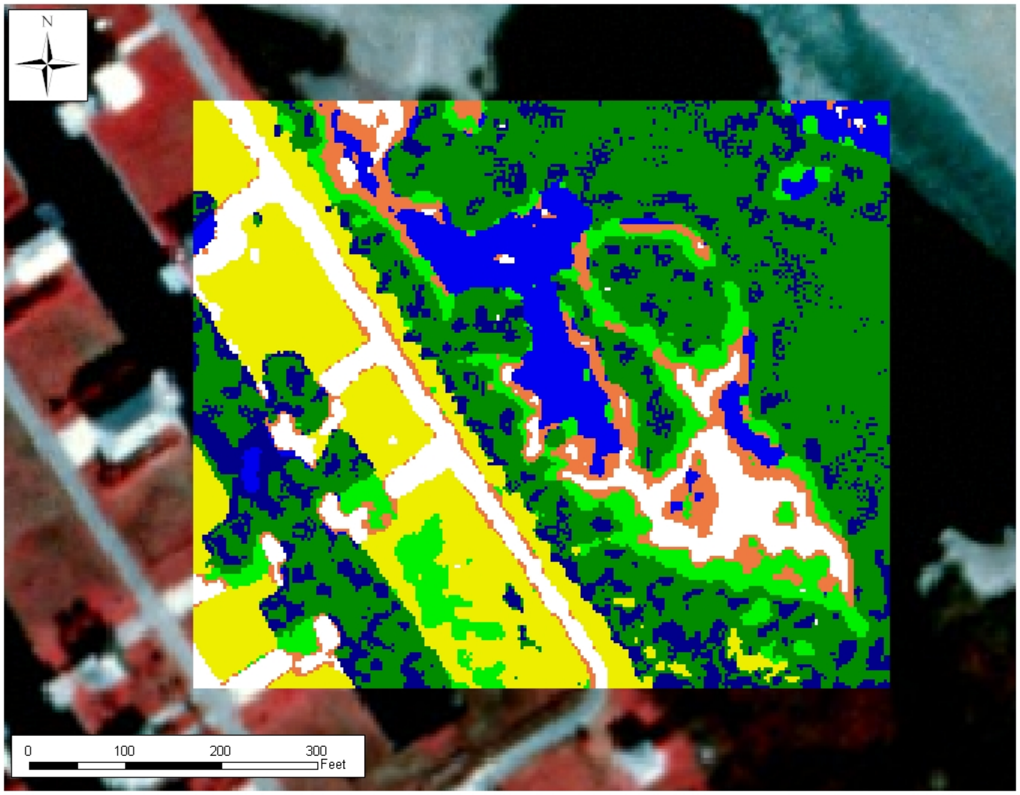


Figure 4. 1995 TNRIS DOQQ photo of southeast Sea Isle quad with Mahalanobis classification map overlaid on top of image.

The percent error output of the ENVI accuracy matrix was run in a three-factor analysis of variance (ANOVA) in SPSS to compute the significance of the data. The percent error of all habitat types was utilized as the dependent variable and the location, year, and classification technique were utilized as the independent variables.

Large-Scale Classification Algorithm Study

Once the accuracy of the small-scale study was given for each classification technique for the habitat type and vegetation community data, the technique with the greatest averaged accuracy was utilized in a large-scale study to distinguish whether the software can identify and classify each habitat type and vegetation community accurately when looking at the entire quad (Hitchcock, Lake Como, and

Sea Isle), not just a certain area within the quad. The ROIs and ground truth points used in the small-scale study were used again as the sample points on the entire quad. All of the GPS points for each quadrangle (i.e. Lake Como 2 and Lake Como 3 for the Lake Como quad) were used to classify each quadrangle. Once classification was complete on the quad, an accuracy matrix and two-factor ANOVA were run on the quad data in order to determine whether differences in accuracy existed among quads and years. The results of the small-scale and large-scale study were compared to see if any accuracy was lost when looking at a larger scale image rather that the site specific area detailed in the small-scale study. Types of errors (omission and commission) for each vegetation community and each habitat type were evaluated to determine where problems occurred in proper classification.

RESULTS

Small-Scale Classification Algorithm Study

The Mahalanobis Distance Classification Algorithm, Maximum Likelihood Classification Algorithm, and Minimum Distance to Means Classification Algorithm produced similar overall accuracies throughout the small-scale study for habitat type and vegetation community analyses (Table 1). Thus, there were no significant difference ($P<0.05$) in accuracy of classification of habitat types or vegetation communities for these three algorithms (Tables 2 and 3). The accuracies for these three algorithms, whether classifying habitat type or vegetation community, ranged from a low of 51% to a high of 65% for year, location, and algorithm. The Parallelepiped Classification Algorithm generated such a low accuracy that there was a significant difference ($P<0.05$) in this algorithm (Tables 2 and 3) from the other three.

The year and location on imagery were not significantly different ($P<0.05$) in classification accuracy for habitat type and vegetation communities (Tables 2 and 3). There were no significant interactions among classification, year, and location. However, there were large variations by quad and year (Table 1). For example, accuracies by algorithm and habitat type for the 1995 aerial classification ranged from 34.2% for the Parallelepiped Classification Algorithm to 58.7% for the Mahalanobis Distance Classification Algorithm. The accuracies for the 2002 aerial classification ranged from 20% to 58%. The highest accuracy in the 1995 aerial habitat type classification for any site was generated using the Minimum Distance to Means Classification Algorithm (73.3% in Sea Isle 1) and the lowest using the Maximum Likelihood Classification Algorithm (13.3% in Lake Como 3). In the 2002 aerial habitat classification, the highest accuracy for a location and year was generated using the Maximum Likelihood Classification Algorithm (81.3%) and the lowest using the Parallelepiped Classification Algorithm (16.7%). In the 1995 aerial vegetation community classification, the highest accuracy was generated using the Mahalanobis Distance Classification Algorithm (84%) and the lowest using the Parallelepiped Classification Algorithm (6.7%). In the 2002 vegetation community classification the highest accuracy that was generated was shared by the Mahalanobis Distance Classification Algorithm, the Maximum Likelihood Classification Algorithm, and the Minimum Distance to Means Classification Algorithm (61.5%). The lowest was by the Parallelepiped Classification Algorithm (5.9%).

Sample values (N-value) ranged from 8-31 throughout the small-scale study (Table 1). In the 1995 aerial habitat type classification the N-value ranged from 9-16. In the 2002 aerial habitat type classification the N-value ranged from 9-17. In the 1995 aerial vegetation community classification the N-value ranged from 8-25, and in the 2002 aerial vegetation community classification the N-value ranged from 13-31. Throughout the small-scale study, the trend shows that the higher the N-value, the lower the accuracy (Table 1). This trend is most distinctive in the 2002 aerial vegetation community classification. In this study the lowest N-value in the Hitchcock 3 location (13) generated the highest accuracy (61.5%) while the highest N-value (31) in Sea Isle 3 generated the lowest accuracy (5.9%).

Table 1. Accuracy of classification of habitat type and vegetation community for each randomly selected location for imagery from year 1995 and 2002.

Year	Sample Location	N	[1]MAHAL-ANOBIS[a]	MAXIMUM[a] LIKELIHOOD	MINIMUM[a] DISTANCE	PARALLEL-EPIPED[b]
Habitat Type						
1995	Hitchcock 2	9	55.60%	44.40%	50.00%	22.20%
1995	Hitchcock3	13	61.54%	69.23%	69.23%	53.85%
1995	LakeComo2	16	68.75%	68.75%	62.50%	37.50%
1995	LakeComo3	15	53.33%	13.33%	46.67%	26.67%
1995	SeaIsle1	15	66.67%	66.67%	73.33%	40.00%
1995	SeaIsle3	15	46.67%	46.67%	40.00%	25.00%
1995	Average		58.76%	51.51%	56.96%	34.20%
2002	Hitchcock 3	14	50.00%	64.29%	57.14%	21.43%
2002	LakeComo2	15	68.75%	81.25%	75.00%	25.00%
2002	LakeComo3	16	37.50%	40.00%	29.41%	17.65%
2002	SeaIsle1	9	50.00%	40.00%	44.44%	20.00%
2002	SeaIsle3	17	64.71%	64.71%	47.06%	16.67%
2002	Average		54.19%	58.05%	50.61%	20.15%
	Combined average		56.68%a	54.48%a	54.07%a	27.81%b
Vegetation Community						
1995	Hitchcock2	25	84.00%	75.00%	83.33%	6.67%
1995	Hitchcock3	8	50.00%	62.50%	62.50%	62.50%
1995	LakeComo2	21	57.14%	9.52%	57.14%	42.86%
1995	LakeComo3	19	68.42%	68.42%	73.68%	21.05%
1995	SeaIsle1	21	47.62%	9.52%	33.33%	9.52%
1995	SeaIsle3	10	80.00%	80.00%	80.00%	40.00%
1995	Average		64.53%	50.83%	65.00%	30.43%
2002	Hitchcock3	13	61.54%	61.54%	61.54%	23.08%
2002	LakeComo2	20	30.00%	60.00%	35.29%	16.67%
2002	LakeComo3	17	47.06%	52.63%	47.37%	10.53%
2002	SeaIsle1	30	30.00%	30.00%	23.33%	13.33%
2002	SeaIsle3	31	32.26%	44.44%	38.24%	5.88%
2002	Average		40.17%	49.72%	41.15%	13.90%
	Combined average		53.45%a	50.32%a	54.159%a	22.91%b

[1] Means with different letters are significantly different as determined by ANOVA and S-N-K mean separation test at $P<0.05$.

Table 2. Analysis variance test results for habitat type classification accuracy. Student-Neuman-Keuls mean separation test was run to determine which of the software algorithms were significantly different from each other. There were no differences between years or among locations.

A. ANOVA

Tests of Between-Subjects Effects

Dependent Variable: Habitat

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Model	110167.771[a]	24	4590.324	13.609	.000
Class	6050.667	3	2016.889	5.980	.004
Year	181.044	1	181.044	.537	.472
Location	110.419	2	55.209	.164	.850
Class * Year	601.692	3	200.564	.595	.626
Class * Location	169.737	6	28.290	.084	.997
Year * Location	95.972	2	47.986	.142	.868
Class * Year * Location	298.366	6	49.728	.147	.987
Error	6745.882	20	337.294		
Total	116913.654	44			

a. R Squared = .942 (Adjusted R Squared = .873)

B. Means separation test for Class

Habitat

Student-Newman-Keuls[a,b]

Class	N	Subset	
		1	2
Parallelepiped	11	27.8155	
Minimum Distance	11		54.0709
Maximum Likelihood	11		54.4818
Mahalanobis	11		56.6836
Sig.		1.000	.941

Means for groups in homogeneous subsets are displayed.
Based on Type III Sum of Squares
The error term is Mean Square(Error) = 337.294.

a. Uses Harmonic Mean Sample Size = 11.000.

b. Alpha = .05.

Table 3. Analysis of variance test results for vegetation community classification accuracy. Student-Neuman-Keuls mean separation test was run to determine which of the software algorithms were significantly different from each other. There were no significant differences between years or among locations

A. ANOVA

Tests of Between-Subjects Effects

Dependent Variable: Vegetation

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Model	104555.124[a]	24	4356.464	9.005	.000
Class	7228.295	3	2409.432	4.980	.010
Year	1971.726	1	1971.726	4.075	.057
Location	2334.933	2	1167.467	2.413	.115
Class * Year	796.154	3	265.385	.549	.655
Class * Location	207.355	6	34.559	.071	.998
Year * Location	237.935	2	118.968	.246	.784
Class * Year * Location	558.270	6	93.045	.192	.975
Error	9676.128	20	483.806		
Total	114231.252	44			

a. R Squared = .915 (Adjusted R Squared = .814)

B. Means separation test for Class

Vegetation

Student-Newman-Keuls[a,b]

Class	N	Subset 1	Subset 2
Parallelepiped	11	22.9173	
Maximum Likelihood	11		50.3245
Mahalanobis	11		53.4582
Minimum Distance	11		54.1591
Sig.		1.000	.912

Means for groups in homogeneous subsets are displayed.
Based on Type III Sum of Squares
The error term is Mean Square(Error) = 483.806.

a. Uses Harmonic Mean Sample Size = 11.000.

b. Alpha = .05.

Large-Scale Classification Algorithm Study

The Mahalanobis Distance Classification Algorithm was utilized in the large-scale study. Although the Mahalanobis Distance Classification Algorithm accuracy (55.1%) was only 0.01% higher than the overall accuracy of the Minimum Distance to Means Classification Algorithm (55.06%), throughout the study the Mahalanobis Distance Classification Algorithm exhibited higher accuracies per quad and year than the Minimum Distance to Means Classification Algorithm. Thus, the Mahalanobis Distance Classification Algorithm was selected for the large-scale classifications.

During the large-scale study classification accuracies of the habitat types and the vegetation communities were relatively low. The average accuracy among years and quads was 58.4% in the habitat type classification study (Table 4). This was nearly the same as the 57% accuracy of the small-scale study (Table 1). In contrast, the 42.1% accuracy in the vegetation community classification study (Table 4) was much lower than the 53% accuracy in the small-scale study (Table 1).

In the large-scale study, there were no statistically significant differences among years or locations in accuracy for habitat type and vegetation community classifications. This is shown in the ANOVA findings (Tables 5 and 6), in which there are no significant differences at $P<0.05$ in classification accuracy for habitat type and vegetation communities. There were no significant interactions among year and locations.

The accuracies among years and quads ranged from 41.7% to 85.7% when classifying habitat type (Table 4). The 1995 aerial habitat type classification produced an accuracy of 60.2% for the Hitchcock quadrangle, 41.7% for the Lake Como quadrangle, and 55% for the Sea Isle quadrangle, for an average accuracy of 52.3%. The 2002 aerial habitat type classification produced an accuracy of 85.7% for the Hitchcock quadrangle, 51.3% for the Lake Como quadrangle, and 56.7% for the Sea Isle quadrangle, for an average accuracy of 64.6%. The inaccuracies of the Mahalanobis Distance Classification Algorithm for habitat types are shown in Figure 5. The software algorithm has inaccurately classified portions of intertidal irregularly exposed water (E1UBM) in the lower right hand area with irregularly flooded intertidal high marsh (E2EM1P) and irregularly flooded shoreline (E2USP) with scattered areas of upland range (Ur) throughout the area.

The accuracies among years and quads were quite variable in the vegetation community classification. Accuracy data verify that inaccurate classification of vegetation communities occurred across years and location. Average accuracy for all species and both years combined was 42.1% for the vegetation community classification. When looking at the accuracies of the vegetation communities between the years of the aerial images, there were no significant differences. However, overall, the 1995 aerial had a greater overall average of 56.3% compared to 40.9% for the 2002 aerial. The inaccuracies are shown in Figure 6, the 1995 Mahalanobis Distance vegetation community classification map of the Hitchcock quad, in which a large portion of the map located in the central right hand area of the map that should have been classified as water is classified as *Iva frutescens*, a shrub normally found in the areas that delineate the ordinary high water mark. The 1995 aerial vegetation community classification produced an accuracy of 80.1% for the Hitchcock quadrangle, 50% for the Lake Como quadrangle, and 38.6% for the Sea Isle quadrangle, for an average accuracy of 56.3%. The 2002 aerial vegetation community classification produced an accuracy of 41.7% for the Hitchcock quadrangle, 41.4% for the Lake Como quadrangle, and 39.5% for the Sea Isle quadrangle, for an average accuracy of 40.9%.

Table 4. Accuracy of classification of habitat type and vegetation community for each entire quadrangle for imagery from year 1995 and 2002.

HABITAT TYPE				
YEAR	LOCATION	QUAD	CLASS-STYLE	PERCENT ACCURACY
1995	2995484	HITCHCOCK	MAHALANOBIS	60.15%
1995	2994491	LAKE COMO	MAHALANOBIS	41.67%
1995	2995564	SEA ISLE	MAHALANOBIS	55.00%
Yearly average				52.3%
2002	2995484	HITCHCOCK	MAHALANOBIS	85.71%
2002	2994491	LAKE COMO	MAHALANOBIS	51.28%
2002	2995564	SEA ISLE	MAHALANOBIS	56.67%
Yearly average				64.6%
Average for all habitat types and years				58.4%
VEGETATION COMMUNITY				
YEAR	LOCATION	QUAD	CLASS-STYLE	PERCENT ACCURACY
1995	2995484	HITCHCOCK	MAHALANOBIS	80.11%
1995	2994491	LAKE COMO	MAHALANOBIS	50.00%
1995	2995564	SEA ISLE	MAHALANOBIS	38.64%
Yearly average				56.3%
2002	2995484	HITCHCOCK	MAHALANOBIS	41.67%
2002	2994491	LAKE COMO	MAHALANOBIS	41.38%
2002	2995564	SEA ISLE	MAHALANOBIS	39.53%
Yearly average				40.9%
Average for all vegetation communities and years.				42.1%

Table 5. Analysis of Variance – Habitat Type Large-Scale Study

Tests of Between-Subjects Effects

Dependent Variable: Per_acc

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	Hypothesis	20472.705	1	20472.705	56.884	.017
	Error	719.810	2	359.905[a]		
Year	Hypothesis	226.198	1	226.198	3.056	.223
	Error	148.030	2	74.015[b]		
Location	Hypothesis	719.810	2	359.905	4.863	.171
	Error	148.030	2	74.015[b]		
Year * Location	Hypothesis	148.030	2	74.015	.	.
	Error	.000	0	.[c]		

a. MS(Location)

b. MS(Year * Location)

c. MS(Error)

Table 6. Analysis of Variance – Vegetation Community Large-Scale Study

Tests of Between-Subjects Effects

Dependent Variable: per_accu

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	Hypothesis	14145.528	1	14145.528	56.573	.017
	Error	500.083	2	250.041[a]		
Year	Hypothesis	355.278	1	355.278	1.687	.324
	Error	421.087	2	210.543[b]		
Location	Hypothesis	500.083	2	250.041	1.188	.457
	Error	421.087	2	210.543[b]		
Year * Location	Hypothesis	421.087	2	210.543	.	.
	Error	.000	0	.[c]		

a. MS(Location)

b. MS(Year * Location)

c. MS(Error)

The Mahalanobis Distance Classification Algorithm was unable to accurately separate hydrophytic communities (E2EM or E2SS) from water classes (E1UB), non-vegetated shoreline (E1US), and upland range habitats (Ur). Low classification accuracies of habitat types and vegetation communities were associated with high omission (failure to place the correct class label on a particular class) and commission errors (placing a particular class label on an incorrect habitat type class) among classes (Tables 7 and 8; Appendix A-Tables 9-20).

Commission errors and omission errors were generally very high among vegetated habitat type classes (Table 7) with an average 68.8% commission error and 61.9% omission error. Accordingly, only 35.7% of E2EM1N pixels, 39.1% of E2EM1P pixels, and 19.2% E2SSP pixels were correctly classified by the Mahalanobis Distance Classification Algorithm. Although vegetated habitat types (E2EM1N, E2EM1P, and E2SSP) were often labeled as other vegetation communities, these vegetated habitat types were also frequently classified as shoreline (E2US), water (E1UB), or upland range (Ur). For example, only 9 of 34 pixels of E2EM1P were correctly labeled by the Mahalanobis Distance Classification Algorithm. Sixteen pixels were labeled as other vegetation classes, but 3 pixels were labeled as water, 4 as shoreline, and 2 as upland range.

The only habitat type classes that had reasonable accuracies were water classes and the upland urban class. The three water classes that had relatively high accuracies and low omission and commission values included E1UBL at 82.4%, E1UBMx at 90.5%, and E1UBN at 100%. However, there were only two ground truth pixel locations for E1UBN.

The problems in separation of vegetated habitat types from each other and from non-vegetated shoreline habitat types or upland vegetation is further demonstrated in the classification of vegetation communities (Table 8). The classes that comprise areas of non-vegetation (road, water, sediment) produce an average accuracy of 83.0% (N=171). Upland habitat types were correctly recognized 100% (N=4) of the time while roads were recognized correctly 79% (N=24) of the time and water 92% (N=119) of the time. When looking only at vegetation community classes (Table 8), the classes that comprise areas of hydrophytic vegetation (*Baccharis halimifolia, Batis maritima, Borrichia frutescens, Iva frutescens, Juncus roemerianus, Monanthochloe littoralis, Salicornia bigelovii, Salicornia virginica, Spartina* *alterniflora, Spartina patens, and Spartina spartinae*) produce an average accuracy of 37.24% (N=196). Only 2 of 11 vegetation communities (*Iva frutescens* at 66% and *Salicornia virginica* at 50%) exceeded 44% accuracy. Omission percentages for the 11 vegetation communities ranged from 41% to 94% while commission percentages ranged from 34% to 89%. Omission and commission percents were less that 21% for road and water.

The ANOVA for the large-scale study indicated that no significant differences existed by years or locations. Accuracy data in tables 9-20 verify that inaccurate classification of vegetation communities occurred across years and location.

Table 7. Overall accuracy of classification of habitat type for all locations and both years.

HABITAT TYPE												
Water classes	E1 UBL	E1 UBM	E1 UBMX	E1 UBN	SUB TOTAL	E2 EM1N	E2 EM1P	E2 SSP	SUB TOTAL	E2 USN	E2 USP	SUB TOTAL
E1UBL	14	0	0	0	14	0	1	0	1	0	2	2
E1UBM	0	8	0	0	8	1	0	2	3	0	3	3
E1UBMX	0	0	19	0	19	0	2	0	2	0	0	0
E1UBN	0	0	0	2	2	0	0	0	0	0	0	0
SUBTOTAL	14	8	19	2	43	1	3	2	6	0	5	5
Vegetation classes												
E2EM1N	1	0	0	0	1	10	10	1	21	4	0	4
E2EM1P	0	0	0	0	0	1	9	3	13	0	5	5
E2SSP	1	0	0	0	1	2	6	5	13	1	11	12
SUBTOTAL	2	0	0	0	2	13	25	9	47	5	16	21
Shoreline Classes												
E2USN	0	0	0	0	0	1	4	1	6	3	0	3
E2USP	1	1	6	0	8	0	0	0	0	0	17	17
SUBTOTAL	1	1	6	0	8	1	4	1	6	3	17	20
Upland Classes												
UR	0	0	0	0	0	0	2	2	4	0	7	7
UUR	0	0	0	0	0	0	0	0	0	0	4	4
UUY	0	0	0	0	0	0	0	0	0	0	0	0
SUBTOTAL	0	0	0	0	0	0	2	2	4	0	11	11
TOTAL	17	9	25	2	53	15	34	14	63	8	49	57
Omission												
Pixels	3	1	6	0	10	5	25	9	39	5	32	37
Percentage	17.6%	11.1%	24.0%	0.0%	18.9%	33.3%	73.5%	64.3%	61.9%	62.5%	65.3%	64.9%

Table 7 (continued)

HABITAT TYPE						COMMISSION		ACCURACY	
Water classes	UR	UUR	UUY	SUB TOTAL	Total	Pixels	%	Pixels	%
E1UBL	0	0	0	0	17	3	17.6%	14	82.4%
E1UBM	3	0	0	3	17	9	52.9%	8	47.1%
E1UBMX	0	0	0	0	21	2	9.5%	19	90.5%
E1UBN	0	0	0	0	2	0	0.0%	2	100.0%
SUBTOTAL	3	0	0	3	57	11	19.3%	43	75.4%
Vegetation classes									
E2EM1N	2	0	0	2	28	18	64.3%	10	35.71%
E2EM1P	5	0	0	5	23	14	60.9%	9	39.13%
E2SSP	0	0	0	0	26	21	80.8%	5	19.23%
SUBTOTAL	7	0	0	7	77	53	68.8%	24	31.17%
Shoreline Classes									
E2USN	0	0	0	0	9	6	66.7%	3	33.3%
E2USP	4	3	1	8	33	16	48.5%	17	51.5%
SUBTOTAL	4	3	1	8	42	22	52.4%	20	47.6%
Upland Classes									
UR	34	5	3	42	53	19	35.8%	34	64.2%
UUR	0	24	0	24	28	4	14.3%	24	85.7%
UUY	4	1	4	9	9	5	55.6%	4	44.4%
SUBTOTAL	38	30	7	75	90	28	31.1%	62	68.9%
TOTAL	52	33	8	93	266	114	42.9%	149	56.0%
Omission									
Pixels	18	9	4	31	117				
Percentage	34.6%	27.3%	50.0%	33.3%	44.0%				

Table 8. Overall accuracy of classification of vegetation community type for all locations and both years.

VEGETATION COMMUNITY	Bac hal	Bat mar	Bor fru	Iva fru	Jun roe	Mon lit	Sal big	Sal vir	Spa alt	Spa pat	Spa Spa	Subtotal Hyd Veg	Upland	Subtotal Upland Veg
Bac hal	1	1	0	1	1	0	2	0	0	0	0	6	0	0
Bat mar	0	5	0	1	0	2	4	0	2	0	0	14	0	0
Bor fru	0	3	8	0	4	0	0	0	4	2	0	21	0	0
Iva fru	0	0	1	21	2	0	2	0	1	0	5	32	0	0
Jun roe	2	0	0	1	7	1	1	3	0	1	0	16	0	0
Mon lit	1	1	0	4	0	1	0	0	0	0	0	7	2	2
Sal big	0	2	3	8	2	1	4	0	2	0	0	22	0	0
Sal vir	0	3	0	1	0	0	1	10	2	0	3	20	0	0
Spa alt	0	3	1	2	0	3	1	4	9	1	0	24	0	0
Spa pat	0	0	0	1	0	0	0	0	1	1	1	4	0	0
Spa spa	0	1	0	5	0	0	8	0	0	0	6	20	0	0
Subtotal	4	19	13	45	16	8	23	17	21	5	15	186	2	2
Upland	0	0	0	0	0	0	0	0	0	0	0	0	4	4
Road	0	2	0	0	0	1	0	0	0	0	0	3	0	0
Water	1	0	0	0	0	1	0	0	0	0	0	2	6	6
Sand	0	2	0	1	0	7	1	0	0	0	0	11	0	0
Subtotal	1	4	0	1	0	9	1	0	0	0	0	16	6	6
TOTAL	5	23	13	46	16	17	24	17	21	5	15	202	12	12
Omission Pixels	4	18	5	25	9	16	20	7	12	4	9	129	8	8
Percentage	80.0%	78.3%	38.5%	54.3%	56.3%	94.1%	83.3%	41.2%	57.1%	80.0%	60.0%	63.9%	66.7%	17.4%

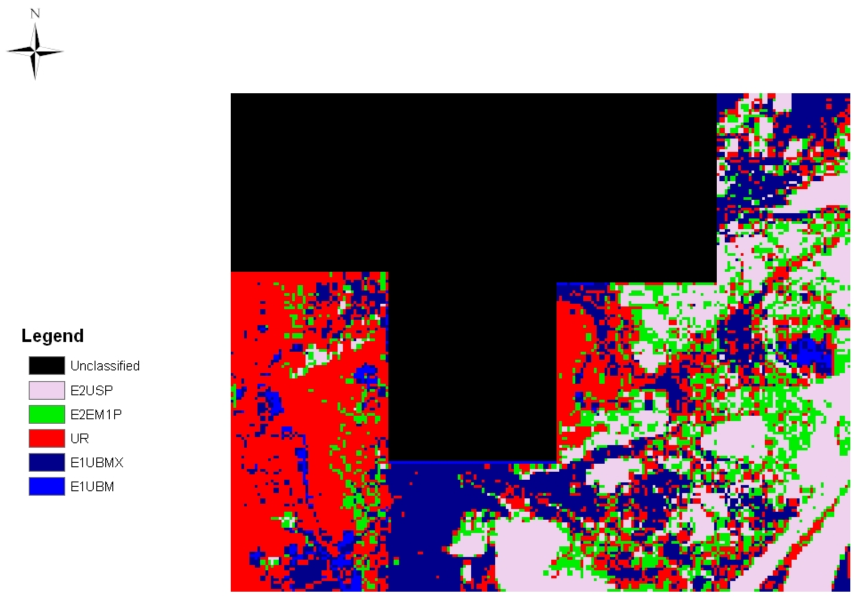
Note: Bac hal = Baccharis halimifolia; Bat mar = Batis maritima; Bor fru = Borrichia frutescens; Iva fru = Iva frutescens; Jun roe = Juncus roemerianus; Mon lit = Monanthochloe littoralis; Sal big = Salicornia bigelovii; Sal vir = Salicornia virginica; Spa alt = Spartina alterniflora; Spa pat = Spartina patens; Spa spa = Spartina spartinae

Table 8 (continued). Overall accuracy of classification of vegetation community type for all locations and both years.

VEGETATION COMMUNITY	Road	Water	Sand	Subtotal Non-veg	Total	Commission Pixels	Commission Percent	Accuracy Pixels	Accuracy Percent
Bac hal	0	0	0	0	6	5	83.3%	1	16.67%
Bat mar	1	0	0	1	15	10	66.7%	5	33.33%
Bor fru	0	0	0	0	21	13	61.9%	8	38.10%
Iva fru	0	0	0	0	32	11	34.4%	21	65.63%
Jun roe	0	0	0	0	16	9	56.3%	7	43.75%
Mon lit	0	0	0	0	9	8	88.9%	1	11.11%
Sal big	0	2	0	2	24	20	83.3%	4	16.67%
Sal vir	0	0	0	0	20	10	50.0%	10	50.00%
Spa alt	0	3	0	3	27	18	66.7%	9	33.33%
Spa pat	0	0	0	0	4	3	75.0%	1	25.00%
Spa spa	0	2	0	2	22	16	72.7%	6	27.27%
Subtotal	1	7	0	8	196	123	62.8%	73	37.24%
Upland	0	0	0	0	4	0	0.00%	4	100%
Road	19	0	2	21	24	5	20.8%	19	79.17%
Water	0	110	1	111	119	9	7.6%	110	92.44%
Sand	3	1	13	17	28	15	53.6%	13	46.43%
Subtotal	22	111	16	149	171	29	17.0%	142	83.04%
TOTAL	23	118	16	157	371	152	41.0%	215	57.95%
Omission									
Pixels	4	8	3	15	152				
Percentage	13.6%	6.8%	18.8%	9.6%	41.0%				

Note: Bac hal = Baccharis halimifolia; Bat mar = Batis maritima; Bor fru = Borrichia frutescens; Iva fru = Iva frutescens; Jun roe = Juncus roemerianus; Mon lit = Monanthochloe littoralis; Sal big = Salicornia bigelovii; Sal vir = Salicornia virginica; Spa alt = Spartina alterniflora; Spa pat = Spartina patens; Spa spa = Spartina spartinae

A.



B.

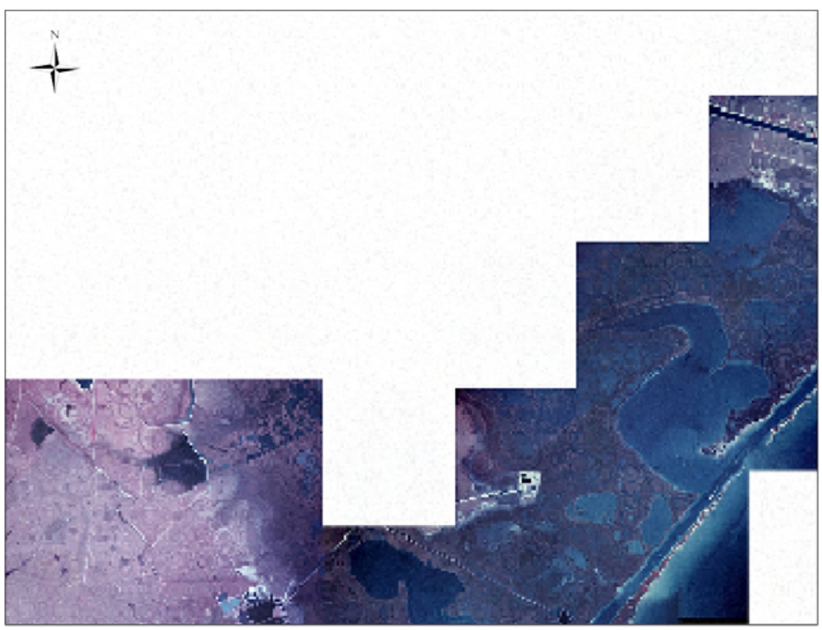
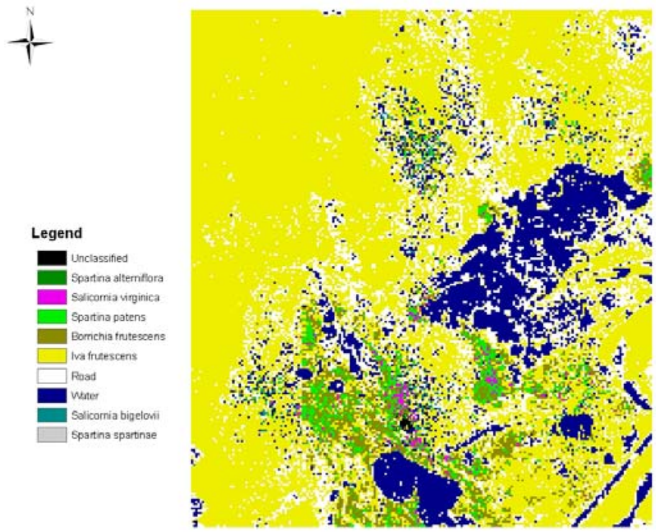


Figure 5. CIR 2002 TGLO imagery (B.) and classified image (A.) of the Hitchcock SE quadrangle showing the different habitat type classifications using the Mahalanobis Distance Algorithm. The accuracy of classification based on ground truth data was 85.71% accurate.

A.



B.

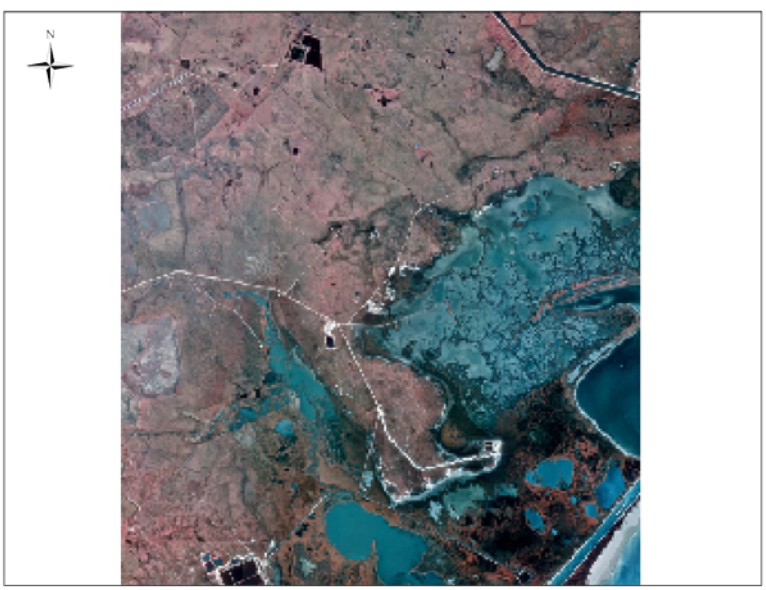


Figure 6. DOQQ CIR 1995 image (B.) and classified image (A.) of the Hitchcock SE quadrangle showing the different vegetation communities using the Mahalanobis Distance Algorithm. The accuracy of classification based on ground truth data was 80.1%

DISCUSSION

Traditionally, Landsat MSS, Landsat TM, and SPOT satellite systems have been utilized in wetland classifications (Sugumaran, 2004). Reasonable classification accuracies with Landsat are sometimes achieved by using low resolution Landsat imagery. Generally the low resolution images are utilized in landscape classifications because of the higher accuracy outputs. But, because of the low spatial resolution of most satellite imagery (20-30m) it is difficult to classify small or narrow wetlands (Ozesmi and Bauer, 2002). Aerial imagery at high resolution is often preferred over satellite imagery for detailed mapping of wetlands (Ozesmi and Bauer, 2002). Of the different types of imagery, color infra-red (CIR) images can be extremely useful when classifying wetlands because it allows recognition of different vegetation associated with differences in soil wetness. It has been demonstrated that, at least in agriculture, spectral patterns of growing vegetation show a uniquely rapid increase in reflectance near the boundary between the red and near infra-red (NIR) bands. Usually, growing vegetation is displayed in red tones on CIR imagery (Dalsted and Queen, 2007). However, in a fragmented marsh, water, vegetation, mud remaining root masses and organic material can confuse and cause overlapping boundaries by the classification software. We used CIR aerial imagery at 0.5 m and 1 m because the aerial imagery used was readily available in high resolutions (0.5 m and 1 m), came in digital form, and were free of charge from a Texas agency.

The changing of resolution of 2002 imagery from 0.5 m to 1 m and georeferencing (aligning) to 1995 imagery did not appear to affect accuracy. This statement is supported by the fact that for habitat type and vegetation community classification, there were no significant differences between years. It was necessary to convert 0.5 m resolution 2002 imagery to 1 m resolution and georeference the 2002 images with the corresponding 1995 image to allow compression of years by locations. The 2002 1 m resolution photography was originally part of a Texas General Land Office (TGLO) image of Galveston Bay that had been merged from numerous small images at 0.5 m resolution. The image was cropped to create panels that entail the same area as the DOQQs. For computer memory considerations and timeliness of classification, the 2002 cropped images were georeferenced using the Nearest Neighbor referencing system within ENVI (2006). Since there were no differences between years and locations, the conversion to 1 m resolution and georeferencing of 2002 images to 1995 images appeared to work without compromising accuracy.

There is the possibility that other software programs such as the Artificial Neural Network (ANN) Classifier could more accurately classify the habitat types and vegetation communities than the software we used. However, the algorithms that we used at the time were readily available in the ENVI software program available to me and were commonly being used for classification at the time of the study. We also wanted to use software that others would have ready access to. Dwivedi et al. (2004) used the ANN Classifier in a land-use/land cover classification over parts of Ethiopia using various spectral band combinations of Landsat TM imagery from 1994 (1:50,000 scale). Similar to our study, their methodology focused on classifying the imagery based on ground truth points and topographical maps of the study area. The Mahalanobis Distance Classification Algorithm, which we used in our study, was not as accurate as the ANN Classifier (Dwivedi et al., 2004) in which accuracy ranged from 78% for band 2, 3, 4 to 97% for all TM bands except 1. Higher accuracies by Dwivedi et al. than in my study can be attributed to the Landsat TM imagery having a much lower resolution than the aerials utilized in this study. The other algorithms that were used generally were not very accurate. The accuracy by Dwivedi with the Mahalanobis Distance Classification Algorithm was low, ranging from 67% for band 2, 4, 5 to 77% for all TM bands. The Maximum Likelihood Classification Algorithm ranged from 68% for bands 2, 3, 4 to 76% for bands 2, 4, 6. The Minimum Distance to Means Classification Algorithm ranged from 67% for bands 2, 3, 4 to 77% for all TM bands except 1. Dwivedi et al. (2004) attributed the higher accuracy of the ANN classifier to heterogeneity inherent in the border pixels of various land-use/land-cover categories, and the multi-modal nature of the Landsat TM data which the ANN classifier could address effectively, but the other techniques could not.

The low accuracy of classification in my study is similar to that found by Sugumaran (2004) and Dwivedi et al. (2004). Sugumaran (2004) found that when classifying wetlands in Iowa using CIR imagery (1 m resolution) the greatest overall accuracy generated using a supervised classification technique (Maximum Likelihood Classification Algorithm) was 57.9%. His methodology also focused on classifying the imagery based on ground truth points, but also relied on NWI (National Wetland Inventory maps). Compared to the Sugumaran study (57.9% accuracy), the overall accuracies generated in the small-scale study (33% to 57% accuracies) and large-scale study (42% to 58%) are similar, but still inaccurate.

Three of the classification algorithms were similar in accuracy, but the Mahalanobis Distance Classification Algorithm yielded the highest overall average accuracy of 55.1% and was arbitrarily chosen for the large-scale study. By using only one algorithm, the large-scale study could be accomplished with the computer resources available. In the small-scale study, the Maximum Likelihood Classification Algorithm yielded an overall average accuracy of 53% and the Minimum Distance to Means Classification Algorithm yielded an overall average of 55.1%. One algorithm appeared particularly unsuitable for classification of the coastal habitat types. The Parallelepiped Classification Algorithm was significantly lower (24.7%) in the small-scale study. The low accuracy of the Parallelepiped Classification Algorithm was to be expected because it is the simplest of the four techniques. It is based on simple Boolean “and/or” logic which can confuse boundaries and classes, rendering inaccuracies within the classification map. These inaccuracies were shown by the low accuracies produced throughout the small-scale study by the Parallelepiped Classification Algorithm.

The inaccuracies in classification appeared to be related to habitat type characteristics. Fragmented marsh, water, vegetation, mud, remaining root masses, and organic material can confuse and cause overlapping boundaries by the classification software. The Mahalanobis Distance Classification Algorithm worked better for classifying the areas that comprise water (81.9%) and uplands (67.9%) than areas that comprise vegetation (36.8%) and shoreline (45%). The higher accuracies in the areas that comprise water and uplands are probably due to the less variability of pixel colors of these habitat types. Water generally has some shade of blue as its pixel color in CIR images, whether it is a dark blue for deep areas or light or aqua blue for shallow areas. There are not many colors that the software algorithm could confuse with these blue colors, so typically the classifications of these areas are accurate. However, deep water areas that have either been dredged (E1UBMx) or are natural (E1UBL) can have a black pixel color, which can overlap with the E2EM1N vegetation areas that have a dark green or black pixel color.

The upland areas generally have a red (vegetation) or white (roads) pixel color in CIR imagery. Not many of the other habitat type classes have a red or white pixel color so the software algorithm was fairly accurate for these habitat types.

The areas that comprise shoreline and vegetation have a variety of overlapping pixel colors on CIR imagery. The vegetation has many shades of brown, green, or yellow on CIR imagery. Generally the hydrophytic vegetation will have a dark green pixel color because it is generally in or near the water. Unfortunately, this dark green can resemble the black pixel color of deep water, so the software algorithm could have confused the vegetation with the deep water and assigned it to the water class. This is where a majority of the inaccuracies occurred in the study. The shoreline areas tend to have a pixel color that is some shade of brown, generally light brown. Some vegetation pixels also have a light brown pixel color, which again could cause some overlap during the classification process. I feel that this is where the inaccuracies occurred for the shoreline areas throughout the study. Thus, the errors in vegetation habitat types (E2EM1N, E2EM1P, and E2SSP) could be due to overlap in water and shoreline signatures. The E2EM1N habitat types are often fragmented or have open vegetation canopies in which water or mud is picked up as part of the spectral signature across a 1 m pixel and across ROIs. The large omission and commission errors and thus low accuracy within the E2EM1N habitat types probably reflect the water and mud within pixels.

The number of ground truth locations may have been a factor in the accuracy generated with the algorithms. In this study a minimum of 2 ground truth points were taken per habitat type class to verify the accuracy. This is not sufficient because of the possible overlap of pixel colors at each ground truth location. In future research studies looking to generate higher accuracies with these software algorithms, I would advise the researcher to take ground truth points all over the entire study area, not just near the original points. I would also advise that the researcher take much more habitat type class points and ground truth points (>100 per class). A larger number of habitat type class points would allow the researcher to easily create the initial ROI classes.

When comparing the classification of areas that comprise vegetation versus non-vegetation, the areas that comprise non-vegetation had the highest accuracy. These high accuracies could be dependent on the low number of pixel colors attributed to these habitat types. Water, roads, sand, and uplands generally only have a few pixel colors assigned to them in CIR imagery. As discussed above with habitat type classes, water will have a pixel the shade of blue, road and sand will have a pixel color the shade of brown or white, and upland will have a pixel color the shade of red. The low accuracies generated by the vegetation community classifications (1995=40.6%, 2002=22.1%) can be attributed to the high number of pixel colors the vegetation community can have in CIR imagery and that the software algorithm could have confused. The vegetation in this study can have a pixel color the shade of brown, yellow, or green. With the overlapping colors throughout the image, the software algorithm could have easily confused or overlapped many designated classes, creating these inaccuracies.

As discussed above, the number of ground truth locations may have been a factor in the accuracy generated with the algorithms. In this study a minimum of 2 ground truth points were taken per vegetation community class to verify the accuracy. This is not sufficient because of the possible overlap of pixel colors at each ground truth location. In future research studies looking to generate higher accuracies with these software algorithms, I would advise the researcher to take ground truth points all over the entire study area, not just near the original points. I would also advise that the researcher take much more habitat type class points and ground truth points (>100 per class). A larger number of vegetation community type class points would allow the researcher to easily create the initial ROI classes.

CONCLUSIONS

The habitat type categories of the Cowardin et al. system (1979) and vegetation communities of the coastal wetlands of GBE could not be accurately classified from 1995 or 2002 CIR imagery at 1m resolution utilizing the Parallelepiped Classification Algorithm, Minimum Distance to Means Classification Algorithm, Maximum Likelihood Classification Algorithm, and Mahalanobis Distance Classification Algorithms that are available in ENVI software. The classification accuracy in the small-scale study varied from 52% to 57% for the habitat type and vegetation community analyses for three algorithms (Minimum Distance to Means Classification Algorithm, Maximum Likelihood Classification Algorithm, and the Mahalanobis Distance Classification Algorithm). The Parallelepiped Classification Algorithm was less accurate (less than 30%) for the habitat type and vegetation community analyses in the small-scale study than the other three algorithms. In small-scale and large-scale studies, the accuracies of each classification method varied considerably among years and locations.

The large-scale study utilized the Mahalanobis Distance Classification Algorithm because it generated the highest overall accuracy in the small-scale study. The large-scale study also demonstrated that habitat type and vegetation communities of the coastal wetlands of GBE can not be accurately classified from CIR imagery using the Mahalanobis Distance Classification Algorithm. The large-scale study produced only 58% accuracy for habitat types and 42% for vegetation communities. The accuracies varied considerably among the sample locations and among the different years of the aerial imagery. Omission and commission errors in the large-scale study were associated with low accuracy levels across locations and imagery years.

Inaccuracies are largely due to overlapping spectral signatures among habitat types and vegetation communities. Overlapping spectral signatures occur because water, vegetation, mud, remaining root masses, and organic material often occur within one habitat type or vegetation community, causing overlapping spectral signatures by the classification software. Soils and water often are seen through overlying vegetation, which causes the programs to improperly classify a habitat type or vegetation community.

The number of ground truth sites was apparently inadequate. For a future research project focusing on the same principles as this study, I would highly recommend that for large area classification, much more ground truth point locations (>100 per class) be taken around the entire study area.

In summary, the overall low accuracies produced by all of the software algorithms in the small-scale study show that these classification methods did not accurately classify habitat types or vegetation communities of the coastal wetlands of GBE.

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APPENDIX A

ACCURACY TABLES – LARGE-SCALE STUDY

Table 9. Habitat Type Classification for 1995 Hitchcock quadrangle aerial.

1995 Habitat Type Hitchcock General Type	Class	E2USP	E1UBM	Ground Truth E2SSP	(Pixels) UR	E1UBMX	E2EM1P	UUR	E1UBN	E2EM1N	Total	Commission (Percent)	Omission (Percent)	Accuracy Percent
Water	E1UBL													-
	E1UBM	3	4	2	3	0	0	0	0	1	13	69.23	20	30.77%
	E1UBMX	0	0	0	0	15	1	0	0	0	16	6.25	28.57	93.75%
	E1UBN	0	0	0	0	0	0	0	2	0	2	0	0	100.00%
	Subtotal	3	4	2	3	15	1	0	2	1	31	32.26%	25.0%	67.74%
Veg	E2EM1N	0	0	0	0	0	1	0	0	1	2	50	50	50.00%
	E2EM1P	2	0	0	4	0	0	0	0	0	6	100	100	0.00%
	E2SSP	10	0	3	0	0	1	0	0	0	14	78.57	40	21.43%
	Subtotal	12	0	3	4	0	2	0	0	1	22	81.82%	66.67%	18.18%
Shore	E2USN													
	E2USP	12	1	0	4	6	0	0	0	0	23	47.83	64.71	52.17%
	Subtotal	12	1	0	4	6	0	0	0	0	23	47.83%	64.71%	52.17%
Upland	UR	7	0	0	27	0	2	5	0	0	41	34.15	28.95	65.85%
	UUR	0	0	0	0	0	0	16	0	0	16	0	23.81	100.00%
	UUY													
	Subtotal	7	0	0	27	0	2	21	0	0	57	24.56%	27.12%	75.44%
	Total	34	5	5	38	21	5	21	2	2	133	39.85%	39.85%	60.15%
Note		Kappa Coefficient		0.514										

Table 10. Habitat Type Classification for 1995 Lake Como quadrangle aerial.

1995 Habitat Type Lake Como														
General		Ground Truth	(Pixels)											
Type	Class	E1UBL	E2EM1N	E2EM1P	E2USP	E2SSP	UR	UUR	E2USN	UUY	Total	Commission	Omission	Accuracy
												(Percent)	(Percent)	Percent
Water	E1UBL	3	0	0	2	0	0	0	0	0	5	40	40	60.00%
	E1UBM													
	E1UBMX													
	E1UBN													
	Subtotal	3	0	0	2	0	0	0	0	0	5	40	40.00%	60.00%
Vegetation	E2EM1N	1	3	3	0	1	1	0	0	0	9	66.67	25	33.33%
	E2EM1P	0	0	4	1	0	0	0	0	0	5	20	66.67	80.00%
	E2SSP	1	1	4	0	0	0	0	1	0	7	100	100	0.00%
	Subtotal	2	4	11	1	1	1	0	1	0	21	66.67%	63.16%	33.33%
Shore	E2USN	0	0	1	0	1	0	0	0	0	2	100	100	0.00%
	E2USP	0	0	0	1	0	0	0	0	0	1	0	75	100.00%
	Subtotal	0	0	1	1	1	0	0	0	0	3	66.67%	80.00%	33.33%
Upland	UR	0	0	0	0	1	0	0	0	0	1	100	100	0.00%
	UUR	0	0	0	0	0	0	3	0	0	3	0	25	100.00%
	UUY	0	0	0	0	0	1	1	0	1	3	66.67	0	33.33%
	Subtotal	0	0	0	0	1	1	4	0	1	7	42.86%	42.86%	57.14%
	Total	5	4	12	4	3	2	4	1	1	36	58.33%	58.33%	41.67%
Note		Kappa Coefficient		0.3316										

Table 11. Habitat Type Classification for 1995 Sea Isle quadrangle aerial.

1995 Habitat Type														
Sea Isle														
General		Ground Truth	(Pixels)											
Type	Class	E1UBM	E2EM1N	E2USN	E2EM1P	E1UBL	UUR	UUY	E2USP	UR	Total	Commission	Omission	Accuracy
												(Percent)	(Percent)	Percent
Water	E1UBL	0	0	0	0	2	0	0	0	0	2	0	0	100.00%
	E1UBM	2	0	0	0	0	0	0	0	0	2	0	0	100.00%
	E1UBMX													
	E1UBN													
	Subtotal	2	0	0	0	2	0	0	0	0	4	0.00%	0.00%	100.00%
Vegetation	E2EM1N	0	1	0	0	0	0	0	0	1	2	50	50	50.00%
	E2EM1P	0	0	0	1	0	0	0	1	0	2	50	0	50.00%
	E2SSP													
	Subtotal	0	1	0	1	0	0	0	1	1	4	50.00%	33.33%	50.00%
Shore	E2USN	0	1	2	0	0	0	0	0	0	3	33.33	0	100.00%
	E2USP	0	0	0	0	0	2	1	0	0	3	100	100	0.00%
	Subtotal	0	1	2	0	0	2	1	0	0	6	66.67%	60.00%	40.00%
Upland	UR	0	0	0	0	0	0	1	0	2	3	33.33	33.33	66.67%
	UUR	0	0	0	0	0	0	0	2	0	2	100	100	0.00%
	UUY	0	0	0	0	0	0	1	0	0	1	0	66.67	100.00%
	Subtotal	0	0	0	0	0	0	2	2	2	6	50.00%	62.50%	50.00%
	Total	2	2	2	1	2	2	3	3	3	20	45.00%	45.00%	55.00%
Note		Kappa Coefficient		0.493										

Table 12. Habitat Type Classification for 2002 Hitchcock quadrangle aerial.

2002 Habitat Type Hitchcock General Type	Class	Ground Truth E2USP	(Pixels) E2EM1P	UR	E1UBMX	E1UBL	Total	Commission (Percent)	Omission (Percent)	Accuracy (Percent)
Water	E1UBL	0	0	0	0	4	4	0	0	100.00%
	E1UBM									
	E1UBMX	0	1	0	4	0	5	0	0	80.00%
	E1UBN									
	Subtotal	0	1	0	4	4	9	11.11%	0.00%	88.89%
Vegetation	E2EM1N									
	E2EM1P	1	2	1	0	0	4	50	33.33	50.00%
	E2SSP									
	Subtotal	1	2	1	0	0	4	50.00%	33.00%	50.00%
Shore	E2USN									
	E2USP	1	0	0	0	0	1	0	50	100.00%
	Subtotal	1	0	0	0	0	1	0.00%	50.00%	100.00%
Upland	UR	0	0	2	0	0	2	0	33.33%	100.00%
	UUR									
	UUY									
	Subtotal	0	0	2	0	0	2	0.00%	33.33%	100.00%
	Total	2	3	3	4	4	16	18.75%	18.75%	81.25%
Note		Kappa Coefficient		0.825						

Table 13. Habitat Type Classification for 2002 Lake Como quadrangle aerial.

2002 Habitat Type Lake Como General Type	Class	Ground Truth E1UBL	(Pixels) E2EM1N	E2EM1P	E2USP	UR	E2SSP	UUR	E2USN	UUY	Total	Commission (Percent)	Omission (Percent)	Accuracy (Percent)
Water	E1UBL	3	0	1	0	0	0	0	0	0	4	25	25	75.00%
	E1UBM													
	E1UBMX													
	E1UBN													
	Subtotal	3	0	1	0	0	0	0	0	0	4	25.00%	25.00%	75.00%
Vegetation	E2EM1N	0	2	5	0	0	0	0	0	0	7	71.43	50	28.57%
	E2EM1P	0	1	1	0	0	1	0	0	0	3	66.67	90.91	33.33%
	E2SSP	0	1	1	0	0	1	0	0	0	3	66.67	66.67	33.33%
	Subtotal	0	4	7	0	0	2	0	0	0	13	69.23%	77.78%	30.77%
Shore	E2USN	0	0	3	0	0	0	0	1	0	4	75	0	25.00%
	E2USP	1	0	0	3	0	0	1	0	0	5	40	25	60.00%
	Subtotal	1	0	3	3	0	0	1	1	0	9	55.56%	20.00%	44.44%
Upland	UR	0	0	0	0	1	1	0	0	0	2	50	50	50.00%
	UUR	0	0	0	1	0	0	2	0	0	3	33.33	50	66.67%
	UUY	0	0	0	0	1	0	0	0	2	3	33.33	0	66.67%
	Subtotal	0	0	0	1	2	1	2	0	2	8	37.50%	37.50%	62.50%
	Total	4	4	11	4	2	3	4	1	2	35	51.43%	54.29%	45.71%
Note		Kappa Coefficient		0.4587										

Table 14. Habitat Type Classification for 2002 Sea Isle quadrangle aerial.

2002 Habitat Type Sea Isle General		Ground Truth	(Pixels)												
Type	Class	E1UBM	E2EM1N	E2USN	E2EM1P	E2USP	E2SSP	UR	UUR	E1UBL	UUY	Total	Commission	Omission	Accuracy
													(Percent)	(Percent)	(Percent)
Water	E1UBL	0	0	0	0	0	0	0	0	2	0	2	0	0	100.00%
	E1UBM	2	0	0	0	0	0	0	0	0	0	2	0	0	100.00%
	E1UBMX														
	E1UBN														
	Subtotal	2	0	0	0	0	0	0	0	2	0	4	0.00%	0.00%	100.00%
Vegetation	E2EM1N	0	3	4	1	0	0	0	0	0	0	8	62.5	0	37.50%
	E2EM1P	0	0	0	1	0	2	0	0	0	0	3	66.67	50	33.33%
	E2SSP	0	0	0	0	1	1	0	0	0	0	2	50	66.67	50.00%
	Subtotal	0	3	4	2	1	3	0	0	0	0	13	61.54%	37.50%	38.46%
Shore	E2USN	0	0	0	0	0	0	0	0	0	0	0	0	100	0.00%
	E2USP	0	0	0	0	0	0	0	0	0	0	0	0	100	0.00%
	Subtotal	0	0	0	0	0	0	0	0	0	0	0	0.00%	100.00%	0.00%
Upland	UR	0	0	0	0	0	0	2	0	0	2	4	50	50	50.00%
	UUR	0	0	0	0	1	0	0	3	0	0	4	25	0	75.00%
	UUY	0	0	0	0	0	0	2	0	0	0	2	100	100	0.00%
	Subtotal	0	0	0	0	1	0	4	3	0	2	10	50.00%	44.44%	62.50%
	Total	2	3	4	2	2	3	4	3	2	2	27	48.15%	48.15%	51.85%
Note		Kappa Coefficient		0.4587											

Table 15. Vegetation Community Classification for 1995 Hitchcock quadrangle aerial.

1995 Veg Hitchcock General Type	Ground Class		Truth (Pixels) Spa alt	Sal vir	Spa pat	Bor fru	Iva fru	Road	Water	Sal big	Spa spa	Total	Commission (Percent)	Omission (Percent)	Accuracy Percent
Veg	Spa	alt	2	0	1	0	0	0	0	0	0	3	33.33	80	66.67%
	Sal	vir	2	8	0	0	0	0	0	0	3	13	38.46	0	61.54%
	Spa	pat	1	0	1	0	0	0	0	0	1	3	66.67	75	33.33%
	Bor	fru	3	0	2	5	0	0	0	0	0	10	50	0	50.00%
	Iva	fru	0	0	0	0	17	0	0	2	4	23	26.09	39.29	73.91%
	Sal	big	2	0	0	0	6	0	0	2	0	10	80	75	20.00%
	Spa	spa	0	0	0	0	5	0	0	4	3	12	75	72.73	25.00%
	Subtotal		10	8	4	5	28	0	0	8	11	74	51.35%	48.65%	51.35%
Road	road		0	0	0	0	0	7	0	0	0	7	0	0	100.00%
	Subtotal		0	0	0	0	0	7	0	0	0	7	0.00%	0.00%	100.00%
Water	water		0	0	0	0	0	0	100	0	0	100	0	0	100.00%
	Subtotal		0	0	0	0	0	0	100	0	0	100	0.00%	0.00%	100.00%
		Total	10	8	4	5	28	7	100	8	11	181	20.99%	19.89%	80.11%
Note			Kappa Coefficient		0.6992										

Note: Spa alt = Spartina alterniflora; Sal vir = Salicornia virginica; Spa pat = Spartina patens; Bor fru = Borrichia frutescens; Iva fru = Iva frutescens;
Sal big = Salicornia bigelovii; Spa spa = Spartina spartinae

Table 16. Vegetation Community Classification for 1995 Lake Como quadrangle aerial.

1995 Veg Lake Como																
General Type		Ground Class	Truth Spa alt	(Pixels) Bat mar	Jun roe	Mon lit	Iva fru	Bor fru	Bac ham	Road	Water	Sand	Total	Commission (Percent)	Omission (Percent)	Accuracy Percent
Veg	Spa	alt	3	2	0	0	1	1	0	0	3	0	10	70	0	30.00%
	Bat	mar	0	1	0	1	0	0	0	0	0	0	2	50	83.33	50.00%
	Jun	roe	0	0	3	1	0	0	1	0	0	0	5	40	50	60.00%
	Mon	lit	0	1	0	1	1	0	0	0	0	0	3	66.67	83.33	33.33%
	Iva	fru	0	0	1	0	2	0	0	0	0	0	3	33.33	50	66.67%
	Bor	fru	0	1	2	0	0	2	0	0	0	0	5	60	33.33	40.00%
	Bac	hal	0	1	0	0	0	0	0	0	0	0	1	100	100	0.00%
	Subtotal		3	6	6	3	4	3	1	0	3	0	29	58.62%	58.62%	41.38%
Road	Road		0	0	0	0	0	0	0	3	0	0	3	0	0	100.00%
	Subtotal		0	0	0	0	0	0	0	3	0	0	3	0.00%	0.00%	100.00%
Water	Water		0	0	0	0	0	0	0	0	2	0	2	0	66.67	100.00%
	Subtotal		0	0	0	0	0	0	0	0	2	0	2	0.00%	66.67%	100.00%
Sand	Sand		0	0	0	3	0	0	0	0	1	4	8	50	0	50.00%
	Subtotal		0	0	0	3	0	0	0	0	1	4	8	50.00%	0.00%	50.00%
		Total	3	6	6	6	4	3	1	3	6	4	42	50.00%	50.00%	50.00%
Note			Kappa Coefficient		0.4463											

Note: Spa alt = Spartina alterniflora; Bat mar = Batis maritima; Jun roe = Juncus roemerianus; Mon lit = Monanthochloe littoralis; Iva fru = Iva frutescens;
Bor fru = Borrichia frutescens; Bac hal = Baccharis halimifolia

Table 17. Vegetation Community Classification for 1995 Sea Isle quadrangle aerial.

1995 Veg Sea Isle General Type		Ground Class	Truth Bac ham	(Pixels) Iva fru	Sal vir	Spa alt	Jun roe	Spa pat	Bat mar	Bor fru	Mon lit	Sal big	sand	water	upland	road	Total
Veg	Bac	hal	1	1	0	0	0	0	0	0	0	1	0	0	0	0	3
	Iva	fru	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Sal	vir	0	1	2	0	0	0	2	0	0	1	0	0	0	0	6
	Spa	alt	0	0	3	2	0	0	0	0	0	0	0	0	0	0	5
	Jun	roe	1	0	0	0	1	1	0	0	0	1	0	0	0	0	4
	Spa	pat	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
	Bat	mar	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
	Bor	fru	0	0	0	0	1	0	2	1	0	0	0	0	0	0	4
	Mon	lit	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2
	Sal	big	0	0	0	0	0	0	1	0	0	2	0	2	0	0	5
	Subtotal		2	4	5	2	2	1	5	1	0	5	0	2	2	0	31
Road	road		0	0	0	0	0	0	0	0	0	0	1	0	0	1	2
	Subtotal		0	0	0	0	0	0	0	0	0	0	1	0	0	1	2
Water	water		0	0	0	0	0	0	0	0	0	0	0	4	0	0	4
	Subtotal		0	0	0	0	0	0	0	0	0	0	0	4	0	0	4
Sand	Sand		0	0	0	0	0	0	0	0	2	0	1	0	0	2	5
	Subtotal		0	0	0	0	0	0	0	0	2	0	1	0	0	2	5
Upland	upland		0	0	0	0	0	0	0	0	0	0	0	0	2	0	2
	Subtotal		0	0	0	0	0	0	0	0	0	0	0	0	2	0	2
		Total	2	4	5	2	2	1	5	1	2	5	2	6	4	3	44
Note			Kappa Coefficient		0.3382												

Note; Bac hal = Baccharis halimifolia; Iva fru = Iva frutescens; Sal vir = Salicornia virginica; Spa alt = Spartina alterniflora; Jun roe = Juncus roemerianus; Spa pat = Spartina patens; Bat mar = Batis maritima; Bor fru = Borrichia frutescens; Mon lit = Monanthochloe littoralis; Sal big = Salicornia bigelovii

Table 17 (continued)

1995 Veg Sea Isle General Type			Commission (Percent)	Omission (Percent)	Accuracy Percent
Veg	Bac	hal	66.67	50	33.33%
	Iva	fru	0	100	0.00%
	Sal	vir	66.67	60	33.33%
	Spa	alt	60	0	40.00%
	Jun	roe	75	50	25.00%
	Spa	pat	100	100	0.00%
	Bat	mar	100	100	0.00%
	Bor	fru	75	0	25.00%
	Mon	lit	100	100	0.00%
	Sal	big	60	60	40.00%
	Subtotal		70.97%	64.52%	29.03%
Road	road		50	66.67	50.00%
	Subtotal		50.00%	66.67%	50.00%
Water	water		0	33.33	100.00%
	Subtotal		0.00%	33.33%	100.00%
Sand	Sand		80	50	20.00%
	Subtotal		80.00%	50.00%	20.00%
Upland	upland		0	50	100.00%
	Subtotal		0.00%	50.00%	100.00%
		Total	61.36%	61.36%	38.64%

Table 18. Vegetation Community Classification for 2002 Hitchcock quadrangle aerial.

2002 Veg Hitchcock General Type		Ground Class	Truth Sal big	(Pixels) Iva fru	Spa spa	water	road	sand	Total	Commission (Percent)	Omission (Percent)	Accuracy (Percent)
Veg	Sal	big	0	1	0	0	0	0	1	100	100	0.00%
	Iva	fru	0	1	1	0	0	0	2	50	50	50.00%
	Spa	spa	3	0	1	2	0	0	6	83.33	50	16.67%
	Subtotal		3	2	2	2	0	0	9	77.78%	71.43%	22.22%
Water	water		0	0	0	0	0	0	0	0	100	0.00%
	Subtotal		0	0	0	0	0	0	0	0.00%	100.00%	0.00%
Road	road		0	0	0	0	1	0	1	0	0	100.00%
	Subtotal		0	0	0	0	1	0	1	0.00%	0.00%	100.00%
Sand	sand		0	0	0	0	0	2	2	0	0	100.00%
	Subtotal		0	0	0	0	0	2	2	0.00%	0.00%	100.00%
		Total	3	2	2	2	1	2	12	58.33%	58.33%	41.67%
Note		Kappa Coefficient		0.3								

Note; Sal big = Salicornia bigelovii; Iva fru = Iva frutescens; Spa spa = Spartina spartinae

Table 19. Vegetation Community Classification for 2002 Lake Como quadrangle aerial.

2002 Veg Lake Como																	
General		Ground	Truth	(Pixels)													
Type		Class	Spa	Bat	Jun	Mon	Sal	Bor	Iva	Spa					Commission	Omission	Accuracy
			alt	mar	roe	lit	big	fru	fru	spa	sand	water	road	Total	(Percent)	(Percent)	(Percent)
Veg	Spa	alt	0	0	0	3	1	0	0	0	0	0	0	4	100	100	0.00%
	Bat	mar	2	3	0	1	0	0	0	0	0	0	1	7	57.14%	50	42.86%
	Jun	roe	0	0	2	0	0	0	1	0	0	0	0	3	33.33	66.67	66.67%
	Mon	lit	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0.00%
	Sal	big	0	1	2	1	0	2	1	0	0	0	0	7	100	100	0.00%
	Bor	fru	1	0	1	0	0	0	0	0	0	0	0	2	100	100	0.00%
	Iva	fru	1	0	1	0	0	1	1	0	0	0	0	4	75	75	25.00%
	Spa	spa	0	1	0	0	1	0	0	2	0	0	0	4	50	0	50.00%
	Subtotal		4	5	6	5	2	3	3	2	0	0	1	31	74.19%	77.42%	25.81%
Water	water		0	0	0	1	0	0	0	0	1	6	0	8	25	0	75.00%
	Subtotal		0	0	0	1	0	0	0	0	1	6	0	8	25.00%	0.00%	75.00%
Sand	sand		0	1	0	1	1	0	1	0	5	0	0	9	44.44	12.50%	55.56%
	Subtotal		0	1	0	1	1	0	1	0	5	0	0	9	44.44%	12.50%	55.56%
Road	road		0	0	0	0	0	0	0	0	0	0	5	5	0	0	100.00%
	Subtotal		0	0	0	0	0	0	0	0	0	0	5	5	0.00%	0.00%	100.00%
		Total	4	6	6	7	3	3	4	2	6	6	6	53	54.72%	47.17%	45.28%
Note		Kappa Coefficient		0.3587													

Note: Spa alt = Spartina alterniflora; Bat mar = Batis maritima; Jun roe = Juncus roemerianus; Mon lit = Monanthochloe littoralis; Sal big = Salicornia bigelovii; Bor fru = Borrichia frutescens; Iva fru = Iva frutescens; Spa spa = Spartina spartinae

Table 20. Vegetation Community Classification for 2002 Sea Isle quadrangle aerial.

2002 Veg Sea Isle General Type		Ground Class	Truth Bac hal	(Pixels) Iva fru	Sal vir	Spa alt	Bat mar	Jun roe	Bor fru	Sal big	Mon lit	sand	water	road	upland	Total	Commission (Percent)	Omission (Percent)	Accuracy (Percent)
Veg	Bac	hal	0	0	0	0	0	1	0	1	0	0	0	0	0	2	100	100	0.00%
	Iva	fru	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0.00%
	Sal	vir	0	0	0	0	1	0	0	0	0	0	0	0	0	1	100	100	0.00%
	Spa	alt	0	1	1	2	1	0	0	0	0	0	0	0	0	5	60	0	40.00%
	Bat	mar	0	0	0	0	1	0	0	4	0	0	0	0	0	5	80	83.33	20.00%
	Jun	roe	0	0	3	0	0	1	0	0	0	0	0	0	0	4	75	50	25.00%
	Bor	fru	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0.00%
	Sal	big	0	0	0	0	0	0	1	0	0	0	0	0	0	1	100	100	0.00%
	Mon	lit	1	3	0	0	0	0	0	0	0	0	0	0	0	4	100	100	0.00%
	Subtotal		1	4	4	2	3	2	1	5	0	0	0	0	0	22	77.27%	54.55%	18.18%
	water		1	0	0	0	0	0	0	0	0	0	4	0	0	5	20	0	80.00%
	Subtotal		1	0	0	0	0	0	0	0	0	0	4	0	0	5	20.00%	0.00%	80.00%
	Sand		0	0	0	0	1	0	0	0	1	1	0	1	0	4	75	50	25.00%
	Subtotal		0	0	0	0	1	0	0	0	1	1	0	1	0	4	75.00%	50.00%	25.00%
	road		0	0	0	0	2	0	0	0	1	1	0	2	0	6	66.67	33.33	33.33%
	Subtotal		0	0	0	0	2	0	0	0	1	1	0	2	0	6	66.67%	33.33%	33.33%
	upland		0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	100.00%
	Subtotal		0	0	0	0	0	0	0	0	0	0	0	0	2	2	0.00%	0.00%	100.00%
		Total	2	4	4	2	6	2	1	5	2	2	4	3	2	39	64.10%	41.03%	33.33%
Note		Kappa Coefficient		0.3477															

Note: Bac hal = Baccharis halimifolia; Iva fru = Iva frutescens; Sal vir = Salicornia virginica; Spa alt = Spartina alterniflora; Bat mar = Batis maritima; Jun roe = Juncus roemerianus; Bor fru = Borrichia frutescens; Sal big = Salicornia bigelovii; Mon lit = Monanthochloe littoralis

APPENDIX B

COWARDIN WETLAND CODES

E1UBL

E1UBL: E1UB_____L______________

[E] Estuarine, [1] Subtidal, [UB] Unconsolidated Bottom, [L] Subtidal

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.
(1) Subtidal - These habitats are continuously submerged substrate, (i.e. below extreme low water).
[UB] Unconsolidated Bottom - Includes all wetlands and deepwater habitats with at least 25% cover of particles smaller than stones (less than 6-7 cm), and a vegetative cover less than 30%.
[L] Subtidal - The substrate is permanently flooded with tidal water.

E1UBM

E1UBM: E1UB_____M______________

[E] Estuarine, [1] Subtidal, [UB] Unconsolidated Bottom, [M] Irregularly Exposed

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.
(1) Subtidal - These habitats are continuously submerged substrate, (i.e. below extreme low water).
[UB] Unconsolidated Bottom - Includes all wetlands and deepwater habitats with at least 25% cover of particles smaller than stones (less than 6-7 cm), and a vegetative cover less than 30%
[M] Irregularly Exposed - The land surface is exposed by tides less often than daily.

E1UBN

E1UBN: E1UB_____N______________

[E] Estuarine, [1] Subtidal, [UB] Unconsolidated Bottom, [N] Regularly Flooded

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.
(1) Subtidal - These habitats are continuously submerged substrate,

(i.e. below extreme low water).
[UB] Unconsolidated Bottom - Includes all wetlands and deepwater habitat with at least 25% cover of particles smaller than stones (less than 6-7 cm), and a vegetative cover less than 30%.

[N] Regularly Flooded - Tidal water alternately floods and exposes land surface at least once daily.

E2USN

E2USN: E2US_____N______________

[E] Estuarine, [2] Intertidal, [US] Unconsolidated Shore, [N] Regularly Flooded

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.
(2) Intertidal - This is defined as the area from extreme low water to extreme high water and associated splash zone.
[US] Unconsolidated Shore - Includes all wetland habitats having three characteristics:
(1) unconsolidated substrates with less than 75% areal cover of stones, boulders, or bedrock;
(2) less than 30% areal cover of vegetation other than pioneering plants; and
(3) any of the following water regimes: irregularly exposed, regularly flooded, irregularly flooded, seasonally flooded, temporarily flooded, intermittently flooded, saturated, seasonal-tidal, temporary-tidal, or artificially flooded.
Intermittent or intertidal channels of the Riverine System or intertidal channels of the Estuarine System are classified as Streambed. Landforms such as beaches, bars, and flats are included in the Unconsolidated Shore class.
[N] Regularly Flooded - Tidal water alternately floods and exposes land surface at least once daily.

E2USP

E2USP: E2US_____P______________

[E] Estuarine, [2] Intertidal, [US] Unconsolidated Shore, [P] Irregularly Flooded

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.
(2) Intertidal - This is defined as the area from extreme low water to extreme high water and associated splash zone.
[US] Unconsolidated Shore - Includes all wetland habitats having three characteristics

(1) unconsolidated substrates with less than 75% areal cover of stones, boulders, or bedrock;
(2) less than 30% areal cover of vegetation other than pioneering plants; and
(3) any of the following water regimes: irregularly exposed, regularly flooded, irregularly flooded, seasonally flooded, temporarily flooded, intermittently flooded, saturated, seasonal-tidal, temporary-tidal, or artificially flooded.

Intermittent or intertidal channels of the Riverine System or intertidal channels of the Estuarine System are classified as Streambed. Landforms such as beaches, bars, and flats are included in the Unconsolidated Shore class.

[P] Irregularly Flooded - Tidal water floods the land surface less often than daily.

E2EM1N

E2EM1N: E2EM1____N_______________

[E] Estuarine, [2] Intertidal, [EM] Emergent, [1] Persistent, [N] Regularly Flooded

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.

(2) Intertidal - This is defined as the area from extreme low water to extreme high water and associated splash zone.

[EM] Emergent - Characterized by erect, rooted, herbaceous hydrophytes, excluding mosses and lichens. This vegetation is present for most of the growing season in most years. These wetlands are usually dominated by perennial plants.

(1) Persistent - Dominated by species that normally remain standing at least until the beginning of the next growing season. This subclass is found only in the Estuarine and Palustrine systems.

[N] Regularly Flooded - Tidal water alternately floods and exposes land surface at least once daily.

E2EM1P

E2EM1P: E2EM1____P_______________

[E] Estuarine, [2] Intertidal, [EM] Emergent, [1] Persistent, [P] Irregularly Flooded

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.

(2) Intertidal - This is defined as the area from extreme low water to extreme high water and associated splash zone.

[EM] Emergent - Characterized by erect, rooted, herbaceous hydrophytes, excluding mosses and lichens. This vegetation is present for

most of the growing season in most years. These wetlands are usually dominated by perennial plants.
(1) Persistent - Dominated by species that normally remain standing at least until the beginning of the next growing season. This subclass is found only in the Estuarine and Palustrine systems.
[P] Irregularly Flooded - Tidal water floods the land surface less often than daily.

E2SSP

E2SSP: E2SS_____P______________

[E] Estuarine, [2] Intertidal, [SS] Scrub-Shrub, [P] Irregularly Flooded

[E] Estuarine - The Estuarine System describes deepwater tidal habitats and adjacent tidal wetlands with low energy and variable salinity, influenced and often semi-enclosed by land.
(2) Intertidal - This is defined as the area from extreme low water to extreme high water and associated splash zone.
[SS] Scrub-Shrub - Includes areas dominated by woody vegetation less than 6 m (20 feet) tall. The species include true shrubs, young trees (saplings), and trees or shrubs that are small or stunted because of environmental conditions.
[P] Irregularly Flooded - Tidal water floods the land surface less often than daily.

Ur

U: U_______________________

[U] Upland

[U] Upland - All areas not defined as wetland or deepwater habitats.

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